A New Soft-Fusion Approach for Multiple-Receiver Wireless Communication Systems

Ashraf M. Aziz, Ahmed M. ElBakly, Mohamed H.A. Azeem, and Gamal A. Hamid

In this paper, a new soft-fusion approach for multiple-receiver wireless communication systems is proposed. In the proposed approach, each individual receiver provides the central receiver with a confidence level rather than a binary decision. The confidence levels associated with the local receiver are modeled by means of soft-membership functions. The proposed approach can be applied to wireless digital communication systems, such as amplitude shift keying, frequency shift keying, phase shift keying, multi-carrier code division multiple access, and multiple inputs multiple outputs sensor networks. The performance of the proposed approach is evaluated and compared to the performance of the optimal diversity, majority voting, optimal partial decision, and selection diversity in case of binary noncoherent frequency shift keying on a Rayleigh faded additive white Gaussian noise channel. It is shown that the proposed approach achieves considerable performance improvement over optimal partial decision, majority voting, and selection diversity. It is also shown that the proposed approach achieves a performance comparable to the optimal diversity scheme.

Keywords: Decision fusion, binary integrator, spatial diversity, multiple receivers systems.

Ashraf M. Aziz (phone: +20 2 2231 8870, email: amaziz64@ieee.org) was with Electronic Engineering Department, Military Technical College, Cairo, Egypt, and is now with Electronics and Communications Engineering Department, College of Engineering and Technology, Arab Academy for Science, Technology, and Maritime Transport, Cairo, Egypt.

Ahmed M. ElBakly (email: aelbakly1964@yahoo.com) is with Basic and Applied Science Department, Arab Academy for Science, Technology, and Maritime Transport, Cairo, Egypt.

Mohamed H.A. Azeem (email: mhabdazeem@hotmail.com) and Gamal A. Hamid (email: gamalm@hotmail.com) are with the Electrical Engineering Department, Military Technical College, Cairo, Egypt.

I. Introduction

Diversity techniques in digital communication systems employ a number of multiple receivers to receive redundant information and a central receiver to fuse the local receiver decisions. A proper fusion of the multiple receivers information in the central receiver results in improved performance. This is equivalent to a decision system with data fusion [1]-[4]. Diversity techniques are now being employed in a wide variety of applications [5]-[12]. Data fusion with multiple receivers in digital communication systems can be performed in three manners. In the traditional method, the multiple receivers send all observations directly to the central receiver without any processing [13], [14]. In this case, the individual receivers produce samples with very large number of bits per individual receiver observations. Also, the entire system resembles the diversity schemes considered for analog receiver implementations. The receiver observations are then combined in the central receiver to form a final decision on which symbol was transmitted. This method is called optimal diversity. Optimal diversity is considered by the majority of research in this area, such as with the maximal ratio combiner [15]. The receiver structure of optimal diversity schemes is very complicated, and its realization is based on the assumption that the channel attenuations and the phase shifts are known perfectly, which is an unrealistic assumption. In addition, this method is inconvenient for real-time processing and requires a large memory.

In the second method, each local receiver processes its individual observation to derive a preliminary single bit decision (0 or 1) on which the symbol was transmitted. This method is called partial (binary or hard) decision processing [16], [17]. The receiver preliminary decisions are sent to the

central receiver where they are fused for global decision making. This method simplifies the local and central receiver structures at the expense of a loss in performance. The performance is degraded because the central receiver receives partial information (binary decision) and does not receive the individual receiver observations. The advantages in simplified receiver structures, real-time processing, and cost may outweigh the loss in performance.

In the third method, each local receiver obtains a soft-decision (more than one bit) rather than a binary (single bit) decision. Soft-decision method provides a measure of confidence in receiver decisions. In this case, several bits are used to represent the local receiver decisions and the reliabilities of these decisions. This method is used to reduce the performance loss of the binary decision processing compared to that of optimal diversity. Many authors made significant contributions in this area. The optimal decision fusion in the Neyman-Pearson sense is derived in [18] when the local receivers transmit one binary quality information bit in addition to the individual binary receiver decisions. This method uses three different thresholds at each receiver. A binary 1 quality bit indicates "confidence" while a binary 0 quality bit indicates "no confidence." A binary 1 quality bit is sent along with the individual receiver decision when the receiver likelihood ratio is either greater than the upper threshold or lower than the lower threshold. Otherwise, a binary 0 quality bit is sent. In this case, the receiver decisions are called semisoft decisions. To simplify the complicated analysis in [18], the case of identical receivers is considered. The general case of transmitting multiple bits local decisions studied in [19], where the optimum multiple bits local decision is derived using the maximum distance criterion. This entails a subpartitioning of the local decision space. While [19] considered the case of only three thresholds and two bits per decision, the solution is very complicated and requires analytic expression for the functional relationships between the probabilities of error and the receiver thresholds and their derivatives. A multilevel quantization and fusion approach for n sensors are proposed in [20]. This approach uses integer thresholds and is considered as a modified version of the counting rules. A multilevel quantization approach for multisensor distributed detection system is proposed in [21]. In this approach, the fusion center combines the sensor soft decisions and the fusion rule does not take the sensor reliabilities into consideration. Quantization for the decentralized hypothesis testing problem has been discussed in several studies (see [22] for an example). Several others have also made significant contributions. Clearly, the optimum determination of the fusion rule in case of distributed detection systems with soft decisions is hardly tractable, and an analytical solution is not possible [23]-[25]. The optimum structure for fusing multiple bits decisions according to the minimum probability of error is derived in [5].

This entails optimum quantization for obtaining the optimum receivers thresholds and optimum quantization levels. When the receivers are not identical (practical case), the problem of determining the optimum quantization levels and thresholds is much more complicated [26], [27]. Thus, the computational cost in generating the optimal solutions is usually excessive and infeasible for real-time processing.

In this paper, a simple and efficient soft-decision fusion approach for multiple-receiver digital communication systems is proposed. Instead of a one-bit hard decision, we propose that each local receiver provides the fusion center with soft decisions. Each receiver's soft decision represents its degree of confidence in that decision. Unlike the published soft-decision models, the central receiver of the proposed approach combines reliability terms weighted by the corresponding confidence levels to decide which symbol was transmitted. The proposed soft-decision approach can be applied easily to non-identical receivers (practical case). It can also be applied easily to any number of sensors, any type of distributed observations, and any number of bits per decision. These advantages could reduce cost and complexity considerably.

The remainder of this paper is organized as follows. Since the proposed soft-decision approach is based on binary digital communications, a quick review of the optimal binary decision fusion is presented in section II. The proposed soft-decision approach is presented in section III. Performance characteristics of the proposed approach and comparison to other diversity schemes are discussed in section IV. We illustrate the characteristic of the proposed approach in binary noncoherent frequency shift keying (NCFSK) digital communication systems in slow Rayleigh fading and additive white Gaussian noise (AWGN) channels. Nevertheless, the proposed soft-decision approach can be applied to other digital communication systems for other interference types in much the same way. The results show that the proposed approach is simple and efficient. Finally, concluding remarks are given in section V.

II. Review of Decision Fusion in Binary Communication Systems

In binary communication systems, we are interested in discriminating between two message symbols 0 and 1, encoded as two known waveforms $s_0(t)$ and $s_1(t)$. We suppose that we are to process a received signal $r(t)$ in additive noise $n(t)$. This is a binary hypothesis testing problem with two hypotheses: H_0 designating bit 0 and H_1 designating bit 1, that is,

$$H_0 : r(t) = s_0(t) + n(t),$$
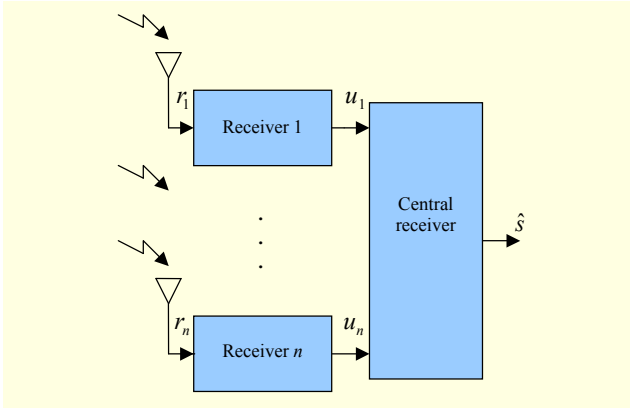$$H_1 : r(t) = s_1(t) + n(t). \tag{1}$$

Fig. 1. Decision fusion in digital communication systems.

We assume that there are n local receivers, as shown in Fig.1, with statistically independent observation $r_1, r_2, ..., r_n$, and have known probability distributions under both hypotheses $f_R(r_i | s_0)$ and $f_R(r_i | s_1)$, $i = 1, 2, ..., n$. It is also assumed that the observation at the i-th receiver is a scalar r_i. The i-th receiver output, $i = 1, 2, ..., n$, is a binary bit decision u_i based only on the observations available at the corresponding receiver.

For each local receiver, the optimum structure should calculate the likelihood ratio and compare it to a likelihood threshold [28]. The binary decision rule at each local receiver can be described as

$$u_i = \begin{cases} 1, & \text{if } LR_i = \dfrac{f_R(r_i | s_1)}{f_R(r_i | s_0)} \geq t_i, \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

where LR_i is the likelihood ratio at the i-th receiver, and the receiver's threshold, t_i, is depending on the criterion of optimality. When the receiver signal-to-noise ratio (SNR) estimates are available, and the receiver's SNR changes so slowly such that the SNR's estimates can be sent to the central receiver with very high precision, the conditional probability distributions in (2) can be replaced by $f_R(r_i | s_0, \gamma_i)$ and $f_R(r_i | s_1, \gamma_i), i = 1, 2, ..., n$, where γ_i is the SNR estimate at receiver i [5].

The binary decisions from the n communication receivers, $u_1, u_2, ..., u_n$, are then sent to a digital central receiver to derive a global decision $\hat{s}$ on which symbol was transmitted. According to the minimum probability of error rate criterion, the optimal decision combining rule for equally likely message bits (ones and zeros equally likely) is the maximum likelihood (ML) decision rule, namely $\hat{s} = 1$ is chosen if [17], [29]

$$\Pr(u_1, u_2, ..., u_n | s_1) > \Pr(u_1, u_2, ..., u_n | s_0). \quad (3)$$

The ratio $\dfrac{\Pr(u_1, u_2, ..., u_n | s_1)}{\Pr(u_1, u_2, ..., u_n | s_0)}$ is called the likelihood ratio

of the set of the individual receiver decisions. By assuming the case of independent receiver observations, the optimal decision rule reduces to

$$\sum_{i=1}^{n} w_i \underset{\hat{s}=0}{\overset{\hat{s}=1}{\gtrless}} 0, \quad (4)$$

where the coefficients $w_i, i = 1, 2, ..., n,$ are given in terms of the probabilities of correct decision (P_{ci}), and the probabilities of bit error (P_{ei}) as

$$w_i = \begin{cases} \ln\left(\dfrac{P_{ci/1}}{P_{ei/0}}\right), & \text{if } u_i = 1, \\ \ln\left(\dfrac{P_{ei/1}}{P_{ci/0}}\right), & \text{if } u_i = 0, \ i = 1, 2, ..., n, \end{cases} \quad (5)$$

$$\begin{aligned} P_{ci/1} &= \Pr(u_i = k | s_k), \\ P_{ei/0} &= \Pr(u_i = 1-k | s_k), \ k = 0, 1. \end{aligned} \quad (6)$$

The optimum fusion rule (4) is interpreted as the sum of the reliabilities of the receiver decisions. The global decision of the central receiver is based on the sign of this sum.

III. Proposed Soft-Decision Diversity Fusion Approach

The main steps of the proposed soft-decision fusion approach are: (1) obtaining the local receiver's soft decisions, and (2) fusing the local receiver's soft decisions. These two steps are illustrated in the following subsections.

1. Obtaining the Local Receiver's Soft Decisions

In the hard-decision case, a one-bit hard decision (0 or 1) is made at each receiver in complete favor of one symbol regardless of the distance between the likelihood function and the receiver's threshold. Thus, the hard-decision case is equivalent to a two-level quantization of the likelihood ratio. However, some receivers may have high confidence levels on their individual decisions such that the decision thresholds are crossed by a large margin. With soft decisions, each sensor would be able to convey its confidence level to the central receiver. This can be done by smoothing the local receiver decisions using a soft-membership function. The soft-membership function of a receiver generates a soft-decision value between 0 and 1 according to the difference between the individual receiver likelihood ratio and the individual receiver threshold.

This can be done by smoothing the local receiver decisions using a soft-membership function μ. The purpose of the soft-membership function is to retain more information and to reduce the performance loss compared to that of the optimal
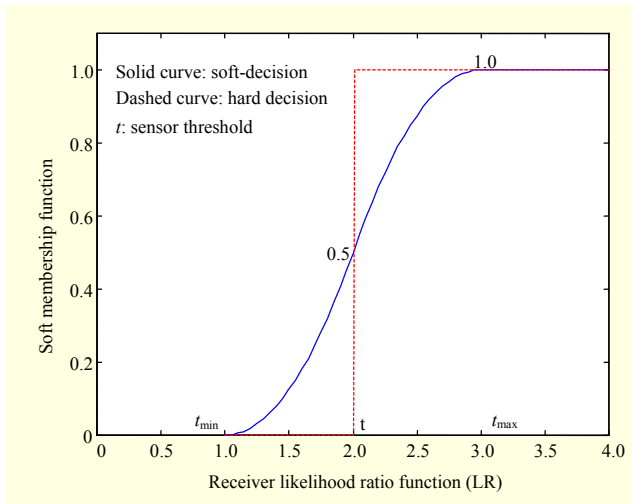
Fig. 2. Membership function.

diversity scheme. For a local receiver i, the value of μ_i is proportional to the degree of confidence in deciding s_0 and s_1. By this way, the receiver likelihood ratio is compressed into the range (0, 1), which makes it possible to be quantized.

The value of the membership function should satisfy the following conditions [1], [13], [30], [31]: (i) the local receiver's decisions are soft values between 0 and 1, that is, $0 \leq \mu_i \leq 1, i = 1, 2, ..., n$, (ii) higher signal levels have a higher grade of membership, (iii) the grade of membership for low signal levels is 0, (iv) the grade of membership for high signal levels is 1, and (v) if a receiver likelihood ratio is equal to the receiver threshold, the value of the membership function will be 0.5. These conditions can be satisfied using a membership function like that shown in Fig. 2 (solid curve). Figure 2 compares the soft-membership and hard-membership (dashed curve) functions. Clearly, the performance of the soft-decision approach depends on the choice of the soft-membership function. The soft-membership function shown in Fig. 2 (solid curve) is appropriate in case of a symmetric probability density function like Gaussian distributed observation. In general, no single best membership function arises for all expected scenarios and different types of probability density functions under hypotheses. Logically, for a given sensor, the soft-membership value depends on the difference between the local likelihood ratio and the sensor's threshold. As shown in Fig. 2, a strip (t_{min}, t_{max}) about the threshold t_i of an individual receiver i is designated as region of no confidence. If the likelihood ratio (LR_i) of receiver i falls into this region, a soft decision μ_i, $0 < \mu_i < 1$, is transmitted. The two regions forming the compliment of the (t_{min}, t_{max}) region are considered confidence regions. When LR_i falls into one of the two confidence regions, μ_i will take the value 0 or 1. It is clear from Fig. 2 that the value

of the soft-membership function μ_i depends on the difference between the likelihood ratio, LR_i, and the receiver threshold t_i. If this difference is low enough ($LR_i \leq t_{min}$), μ_i will take the value 0. If the difference is high enough ($LR_i \geq t_{max}$), μ_i will take the value 1. If $t_{min} < LR_i < t_{max}$, the membership function μ_i takes a value between 0 and 1.

For $LR_i > t_i$ ($\mu_i > 0.5$), the degree of confidence in deciding s_1 is μ_i. For $LR_i < t_i$ ($\mu_i < 0.5$), the degree of confidence in deciding s_0 is $1 - \mu_i$).

The membership function shown in Fig. 2 (solid curve) can be expressed in terms of the local likelihood ratio as

$$\mu_i(LR_i) = \begin{cases} 0, & \text{if } LR_i \leq t_{min}, \\ 2\left[\dfrac{LR_i - t_{min}}{t_{max} - t_{min}}\right]^2, & \text{if } t_{min} \leq LR_i \leq t_i, \\ 1 - 2\left[\dfrac{LR_i - t_{max}}{t_{max} - t_{min}}\right]^2, & \text{if } t_i \leq LR_i \leq t_{max}, \\ 1, & \text{if } LR_i \geq t_{max}, \end{cases} \quad (7)$$

where $t_i = (t_{max} - t_{min})/2$. The actual values of t_{min} and t_{max} depend on the region of no confidence and the expected signal range under s_0 and s_1. In (7), we choose the square of the difference between the receiver's likelihood ratio and the receiver's threshold to achieve a more gradual membership function.

The soft decision at each local receiver i can be described as

$$\mu_i(LR_i) = \begin{cases} 0, & \text{if } LR_i \leq t_{min}, \\ 0 < \mu_i < 0.5, & \text{if } t_{min} \leq LR_i \leq t_i, \\ 0.5 < \mu_i < 1, & \text{if } t_i \leq LR_i \leq t_{max}, \\ 1, & \text{if } LR_i \geq t_{max}, \end{cases} \quad (8)$$

and the corresponding confidence level on deciding s_0 and s_1 will be

$$conf_i = \begin{cases} 1, & \text{if } LR_i \leq t_{min}, \\ 1 - \mu_i, & \text{if } t_{min} \leq LR_i \leq t_i, \\ \mu_i, & \text{if } t_i \leq LR_i \leq t_{max}, \\ 1, & \text{if } LR_i \geq t_{max}. \end{cases} \quad (9)$$

The values of the membership function of the local receivers are quantized and sent to the central digital receiver. A scalar quantizer is used to map the input value of the membership function μ_i into an output variable μ_{ij} ($\in$ the interval [0, 1]), $j = 1, 2, ..., Q$, using a Q-level quantizer. The terminals of each quantization interval j have corresponding thresholds denoted by $t_{i(j-1)}$ and t_{ij} and a corresponding quantizer output μ_{ij}. The lower limit of the quantization intervals is t_0 ($t_0 = t_{min}$), and the upper limit is t_Q ($t_Q = t_{max}$). We do not address the problem of optimum quantization but simply adopt the true values of the

confidence levels, (9), on deciding s_0 and s_1.

2. Fusing Local Receivers Soft Decisions

Let Ω_i^0 be the local soft-decision space for receiver i such that $\mu_i = 0$, Ω_{ij}^0 is the local soft-decision space such that $\mu_i < 0.5$, $j = 1, 2, ..., Q/2$, Ω_{ij}^1 is the local soft-decision space such that $\mu_i > 0.5$, $j = (Q/2 + 1)$, $(Q/2 + 2), ..., Q$, and Ω_i^1 is the local soft-decision space such that $\mu_i = 1$. The soft-decision values are then given as

$$\mu_i = \begin{cases} 0 & (\text{decide } s_0 \text{ with 100\% confidence}) \text{ if } \mu_i \in \Omega_i^0, \\ \mu_{i1} & (\text{decide } s_0 \text{ with higher confidence}) \text{ if } \mu_i \in \Omega_{i1}^0, \\ \\ \mu_{i(Q/2)} & (\text{decide } s_0 \text{ with lower confidence}) \text{ if } \mu_i \in \Omega_{i(Q/2)}^0, \\ \mu_{i((Q/2)+1)} & (\text{decide } s_1 \text{ with lower confidence}) \text{ if } \mu_i \in \Omega_{i((Q/2)+1)}^1, \\ \\ \mu_{iQ} & (\text{decide } s_1 \text{ with higher confidence}) \text{ if } \mu_i \in \Omega_{iQ}^1, \\ 1 & (\text{decide } s_1 \text{ with 100\% confidence}) \text{ if } \mu_i \in \Omega_i^1. \end{cases}$$
(10)

The local binary-decision spaces (Ω_i^+ and Ω_i^-) can be written in terms of the local soft-decision spaces as

$$\Omega_i^+ = \Omega_i^0 \cup \Omega_{i1}^0 \cup \Omega_{i2}^0 \cup .... \cup \Omega_{i(Q/2)}^0,$$
$$\Omega_i^- = \Omega_{i((Q/2)+1)}^1 \cup \Omega_{i((Q/2)+2)}^1 \cup ... \cup \Omega_{iQ}^1 \cup \Omega_i^1, \quad (11)$$
$$\Omega_i^+ \cap \Omega_i^- = \phi.$$

Equation (11) is interpreted as subpartitioning of the local receiver decision space into disjoint soft-decision spaces, that is,

$$\Omega_{im}^k \cap \Omega_{ij}^k = \phi, \ \forall i, \ k = 0,1, \ m \neq j. \quad (12)$$

The central digital receiver implements the ML decision rule using all the receiver's soft-decisions ($\mu = \{\mu_1, ..., \mu_n\}$) that the individual receivers have communicated, that is, it formulates the likelihood ratio function (assuming independent receiver decisions)

$$LR_0(\mu) = \frac{\Pr(\mu \mid s_1)}{\Pr(\mu \mid s_0)} = \prod_{i=1}^{n} \frac{\Pr(\mu_i \mid s_1)}{\Pr(\mu_i \mid s_0)}. \quad (13)$$

If we assume that n_{s_0} number of receivers decide 0, n_1 number of receivers decide μ_{i1}, n_2 number of receivers decide $\mu_{i2}, ..., n_Q$ number of receivers decide μ_{iQ}, and n_{s_1} number of receivers decide 1, and

$$n_{s_0} + n_1 + n_2 + ... + n_Q + n_{s_1} = n, \quad (14)$$

then (13) can be rewritten as

$$LR_0(\mu) = \prod_{i=1}^{n_{s_0}} \frac{P(\mu_i = 0 \mid s_1)}{P(\mu_i = 0 \mid s_0)} \prod_{i=1}^{n_1} \frac{P(\mu_i = \mu_{i1} \mid s_1)}{P(\mu_i = \mu_{i1} \mid s_0)} \prod_{i=1}^{n_2} ...$$
$$... \prod_{i=1}^{n_Q} \frac{P(\mu_i = \mu_{iQ} \mid s_1)}{P(\mu_i = \mu_{iQ} \mid s_0)} \prod_{i=1}^{n_{s_1}} \frac{P(\mu_i = 1 \mid s_1)}{P(\mu_i = 1 \mid s_0)}. \quad (15)$$

The main idea of the proposed approach is to weight each reliability term (in each soft-decision space) in (15) by the corresponding confidence level in deciding hypotheses s_0 and s_1. The sensors confidence levels are determined using (9) in accordance with the distance between the local receiver decision statistics and the receiver thresholds. In this case, the global decision statistic will be a weighted sum of the local receiver decision statistics. Taking the logarithms in (15) and taking into consideration the confidence levels of the sensor soft decisions in (9), the likelihood ratio function can be rewritten as

$$\ln(LR_0(\mu)) = \ln\left(\frac{P(\mu \mid s_1)}{P(\mu \mid s_0)}\right)$$
$$= \sum_{i=1}^{n_{s_0}} \ln\left(\frac{P(\mu_i = 0 \mid s_1)}{P(\mu_i = 0 \mid s_0)}\right)$$
$$+ \sum_{i=1}^{n_1} (1 - \mu_{i1}) \ln\left(\frac{P(\mu_i = \mu_{i1} \mid s_1)}{P(\mu_i = \mu_{i1} \mid s_0)}\right) + ...$$
$$+ \sum_{i=1}^{n_Q} \mu_{i1} \ln\left(\frac{P(\mu_i = \mu_{iQ} \mid s_1)}{P(\mu_i = \mu_{iQ} \mid s_0)}\right)$$
$$+ \sum_{i=1}^{n_{s_1}} \ln\left(\frac{P(\mu_i = 1 \mid s_1)}{P(\mu_i = 1 \mid s_0)}\right). \quad (16)$$

Define

$$P_{ei/s_1} = \Pr(\mu_i = 0 \mid s_1),$$
$$P_{ci/s_0} = \Pr(\mu_i = 0 \mid s_0),$$
$$P_{eij/s_1} = \Pr(\mu_i = \mu_{ij} \mid s_1), \ j = 1, 2, ..., Q/2,$$
$$P_{cij/s_0} = \Pr(\mu_i = \mu_{ij} \mid s_0), \ j = 1, 2, .., Q/2,$$
$$P_{cij/s_1} = \Pr(\mu_i = \mu_{ij} \mid s_1), \ j = \frac{Q}{2} + 1, \frac{Q}{2} + 2, .., Q, \quad (17)$$
$$P_{eij/s_0} = \Pr(\mu_i = \mu_{ij} \mid s_0), \ j = \frac{Q}{2} + 1, \frac{Q}{2} + 2, ..., Q,$$
$$P_{ci/s_1} = \Pr(\mu_i = 1 \mid s_1),$$
$$P_{ei/s_0} = \Pr(\mu_i = 1 \mid s_0),$$

where P_{eij/s_k} and P_{cij/s_k} are the probability of error and probability of correct decision of receiver i, respectively, in quantization interval j given s_k was transmitted, $k = 0,1$. The probability terms P_{ci/s_k} and P_{ei/s_k} have similar definitions in the intervals $[-\infty, t_0]$ and $[t_Q, \infty]$, respectively. From (16) and (17), the decision rule of the central receiver reduces to

$$\sum_{i=1}^{n} c_i \mathop{\underset{\hat{s}=0}{\overset{\hat{s}=1}{\gtrless}}}\; 0, \tag{18}$$

where the coefficients $c_i, i = 1, 2, ..., n$, are given in terms of reliability terms weighted by the soft-decision confidence levels as

$$c_i = \begin{cases} \ln\left(\dfrac{P_{ei/s_1}}{P_{ci/s_0}}\right), & \text{if } \mu_i = 0 , \\[2ex] (1-\mu_{ij})\ln\left(\dfrac{P_{eij/s_1}}{P_{cij/s_0}}\right), & \text{for } j = 1,2,...,\dfrac{Q}{2}, \\[2ex] \mu_{ij}\ln\left(\dfrac{P_{cij/s_1}}{P_{eij/s_0}}\right), & \text{for } j = (\dfrac{Q}{2}+1),...,Q, \\[2ex] \ln\left(\dfrac{P_{ci/s_1}}{P_{ei/s_0}}\right), & \text{if } \mu_i = 1 . \end{cases} \tag{19}$$

For given probability density functions of the observations under both hypotheses ($f_R(r_i \mid s_0)$ and $f_R(r_i \mid s_1)$), the ratios between the reliability terms in (19) can be easily obtained as

$$\frac{P_{ei/s_1}}{P_{ci/s_0}} = \frac{\displaystyle\int_{-\infty}^{t_0} f_R(r_i \mid s_1)\, dr_i}{\displaystyle\int_{-\infty}^{t_0} f_R(r_i \mid s_0)\, dr_i}, \tag{20a}$$

$$\frac{P_{eij/s_1}}{P_{cij/s_0}} = \frac{\displaystyle\int_{t_{j-1}}^{t_j} f_R(r_i \mid s_1)\, dr_i}{\displaystyle\int_{t_{j-1}}^{t_j} f_R(r_i \mid s_0)\, dr_i}, \quad j = 1,2,...,\frac{Q}{2}, \tag{20b}$$

$$\frac{P_{cij/s_1}}{P_{eij/s_0}} = \frac{\displaystyle\int_{t_{j-1}}^{t_j} f_R(r_i \mid s_1)\, dr_i}{\displaystyle\int_{t_{j-1}}^{t_j} f_R(r_i \mid s_0)\, dr_i}, \quad j = \frac{Q}{2}+1,..,Q, \tag{20c}$$

$$\frac{P_{ci/s_1}}{P_{ei/s_0}} = \frac{\displaystyle\int_{t_Q}^{\infty} f_R(r_i \mid s_1)\, dr_i}{\displaystyle\int_{t_Q}^{\infty} f_R(r_i \mid s_0)\, dr_i}. \tag{20d}$$

In the case of equiprobable transmitted bits, that is, $\Pr(s_0$ sent$) = \Pr(s_1$ sent$) = 0.5$, the performance of the central receiver is evaluated in terms of the probability of error bit as

$$P_e = \frac{1}{2}[\Pr(\sum_{i=1}^{n} c_i \geq 0 | s_0) + \Pr(\sum_{i=1}^{n} c_i < 0 | s_1)]$$

$$= \frac{1}{2}[\int_{\sum_{i=1}^{n} c_i \geq 0} f_{c_i}(\sum_{i=1}^{n} c_i | s_0) + \int_{\sum_{i=1}^{n} c_i < 0} f_{c_i}(\sum_{i=1}^{n} c_i | s_1)], \tag{21}$$
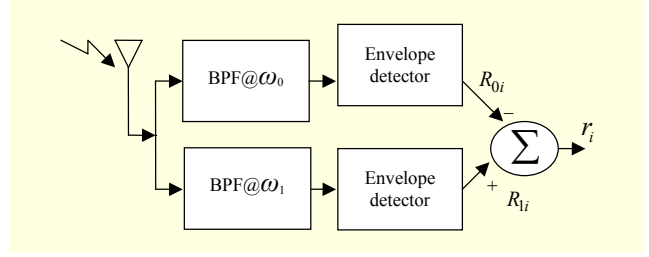

Fig. 3. Block diagram of each individual receiver in case of NCFSK.

where $f_{c_i}(\sum c_i \mid s_k)$ is the probability density function of the sum of the coefficients c_i, $i = 1, 2, ..., n$, given s_k was transmitted, and $k = 0, 1$. The integrals in (20) cannot be easily evaluated; therefore, no analytic expression for the probability of error can be easily obtained. Instead, the error rate probability is estimated using Monte-Carlo simulation.

IV. Performance Comparison with Other Diversity Combining Schemes

This section compares the performance of the proposed soft-decision approach to some diversity schemes assuming that n receivers are employed to achieve a diversity gain. We consider the case of NCFSK in a nonselective slow Rayleigh fading channel corrupted by AWGN, where the fading is assumed to be slow enough so that it can be assumed constant over several bit periods. We consider cases with independent noise (and fading) from receiver to receiver [5]. We also assume that no estimates of the receiver SNR's is available.

Consider a multipath environment where binary NCFSK is to be employed. Each individual receiver employs the structure of binary NCFSK receiver [15], as shown in Fig. 3.

In a slow Rayleigh fading channel, the probability density function of the received SNR is given by [5]

$$f_{\Gamma}(\gamma_i) = \frac{1}{\gamma_0} e^{-\frac{\gamma_i}{\gamma_0}}, \quad \gamma_i \geq 0, \; i = 1, 2, ..., n, \tag{22}$$

where γ_0 is the average SNR. The probability of error in case of a single channel NCFSK in slow Rayleigh fading is [15]

$$P_e = \frac{1}{2 + \gamma_0}. \tag{23}$$

The likelihood ratio is written as

$$LR_i = \frac{f_R(r_i \mid s_1)}{f_R(r_i \mid s_0)} = \frac{\displaystyle\int_{\gamma_i=0}^{\infty} f_R(r_i \mid s_1, \gamma_i)\, f_{\Gamma}(\gamma_i)\, d\gamma_i}{\displaystyle\int_{\gamma_i=0}^{\infty} f_R(r_i \mid s_0, \gamma_i)\, f_{\Gamma}(\gamma_i)\, d\gamma_i}, \tag{24}$$

where [5]

$$f_R(r_i \mid s_1, \gamma_i) = \int_{r=-r_i}^{\infty} r \exp(-\frac{r^2}{2}) \exp(-\gamma_i)$$
$$\times I_0((r+r_i)\sqrt{2\gamma_i})(r+r_i)\times\exp(-\frac{(r+r_j)^2}{2})dr,$$

(25)

$$f_R(r_i \mid s_0, \gamma_i) = \int_{r=-r_i}^{\infty} r \exp(-\frac{r^2}{2}) \exp(-\gamma_i)$$
$$\times I_0(r\sqrt{2\gamma_i})(r+r_i)\times\exp(-\frac{(r+r_j)^2}{2})dr. \ (26)$$

The performance of binary NCFSK with maximal ratio combiner (MRC) (optimal diversity) can be expressed as [15]

$$P_{e\_MRC} = [0.5(1-\xi)]^n \sum_{k=0}^{n-1} \binom{n-1+k}{k}[0.5(1+\xi)]^n, \quad (27)$$

where by definition

$$\xi = \frac{\gamma_0}{2+\gamma_0}. \quad (28)$$

In the case of a majority voting combiner, in which the central receiver decides in favor of the majority of the n local receivers, the probability of error is [17]

$$P_{e\_mv} = \left(G - \frac{n-1}{2}\right)\binom{n}{G}P_e^{n/2}(1-P_e)^{n/2}$$
$$+ \sum_{k=G+1}^{n}\binom{n}{k}P_e^k(1-P_e)^{n-k}, \quad (29)$$

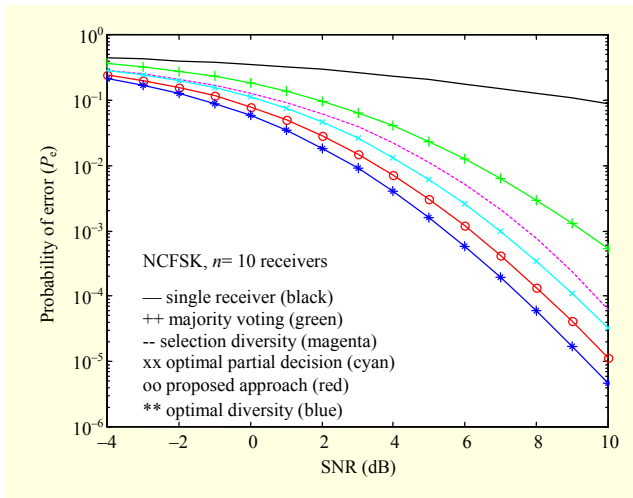where G is the greatest integer $\leq n/2$, and $\binom{n}{G}$ is the binomial coefficient.

In the case of selection diversity, in which the central receiver decision is based on only the channel with the highest SNR, the probability of error is [32], [33]

$$P_{e\_sel} = \frac{n!}{2\prod_{k=1}^{n}(k+\frac{\gamma_0}{2})}. \quad (30)$$

In the case of optimal partial decision combining, the expression for the probability of error cannot be easily evaluated. However, an upper bound can be obtained on the probability of error when binary NCFSK is used [17], namely,

$$P_{e\_OPD} \leq \frac{1}{(2+\gamma_0)^n}\sum_{k=1}^{n}\left\{\binom{2n-k-1}{n-1}\left[(-1)^n 2^{k-n}+2^n\left(\frac{2+\gamma_0}{4+\gamma_0}\right)^{n-k}\right]\right.$$
$$+\sum_{j=1}^{n-1}(-1)^{n-j}\binom{n}{j}\sum_{i=0}^{n-k}2^{j-i}\binom{n-k+j-i-1}{j-1}$$
$$\left.\times\binom{n-j+i-1}{i}\left(\frac{2+\gamma_0}{4+\gamma_0}\right)^{n-k-i}\right\}.$$

(31)

The membership function defined by (7) is generated within the ambiguous interval. The ambiguous interval is defined by considering $\pm 20\%$ uncertainty region about the sensor thresholds [34]. We can also define the ambiguous interval in terms of the expected interference levels [29], [35].

The bit error rate performance versus SNR curves of a single receiver, the majority voting combiner, the selection diversity combiner, the optimal partial decision scheme, the proposed soft-decision approach, and the optimal diversity scheme, for different number of receivers, are shown in Figs. 4 through 6. In Fig. 4, we assume that the number of receivers is ten (n=10).

Fig. 4. Bit error rates versus SNR of each individual receiver in case of NCFSK, n=10.
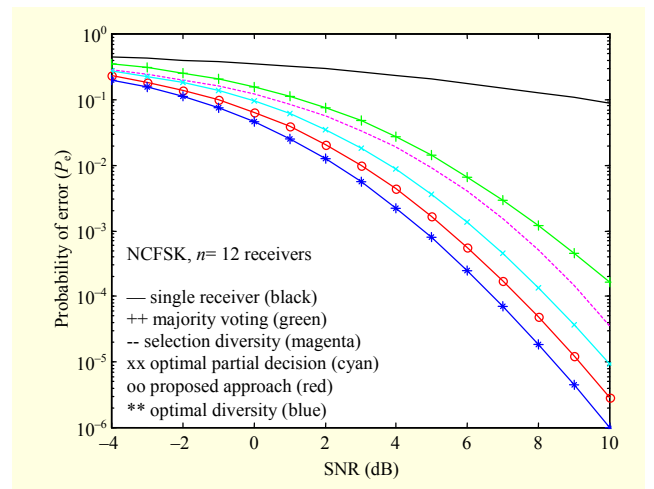

Fig. 5. Bit error rates versus SNR of each individual receiver in case of NCFSK, n=12.
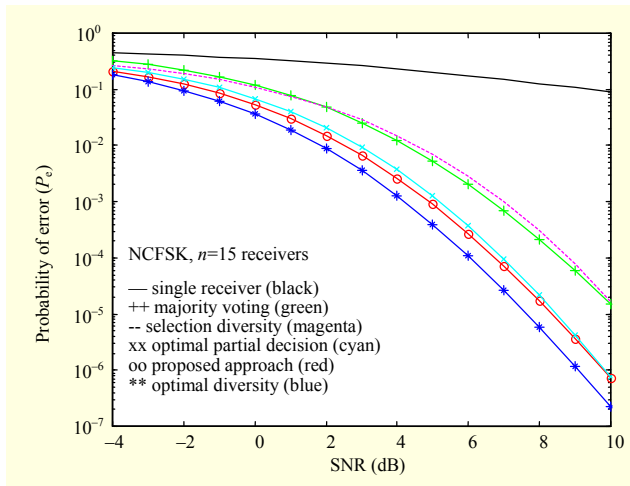
Fig. 6. Bit error rates versus SNR of each individual receiver in case of NCFSK, n=15.

Figure 4 shows the performance improvement of the majority voting combiner, selection diversity combiner, optimal partial decision scheme, proposed approach, and optimal diversity scheme over the single receiver performance. The performance loss between the optimal diversity scheme and all other diversity schemes is obvious. The performance improvement of the proposed approach over the majority voting combiner, selection diversity combiner, and optimal partial decision scheme is also obvious. It is clear that the proposed approach reduces the performance loss compared to that of the optimal diversity scheme. Figures 5 and 6 show the same results for 12 and 15 receivers, respectively. These results could simplify the receiver structures and reduce the complexity. These results are also consistent with those obtained for multiple receivers diversity with optimum quantization [1] and for optimum distributed detection problem [19].

V. Conclusion

A soft-decision diversity combining approach for multiple-receiver digital communication systems has been proposed. In this approach, the reliability terms of local receivers are weighted by the measures of confidence in the local receiver soft-decisions. The confidence levels are based on soft-membership functions, which can be chosen according to the underlying process. The fusion rule of the central receiver, based on the soft-membership functions, has been derived. Performance evaluation of the proposed approach has been provided and compared to the performance of the optimum diversity scheme, optimal partial decision scheme, majority voting combiner, and selection diversity combiner in case of binary NCFSK in slow Rayleigh fading. It has been shown that the performance of the proposed soft-decision approach is

better than the performance of the majority voting combiner, selection diversity combiner, and optimal partial decision scheme. It has been also shown that the performance of the proposed approach is reasonably close to the optimal diversity scheme. These results could reduce cost and complexity considerably.

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Ashraf M. Aziz received the BS and MS in electrical engineering from the Military Technical College, Cairo, Egypt, in 1987 and 1992, respectively. He received the PhD in electrical engineering from the Naval Postgraduate School, Monterey, California, USA, in 1999. He is currently working as a professor in the Electronics and Communications Engineering Department in the Arab Academy for Science, Technology & Maritime Transport, Cairo, Egypt. His research interests include communication systems, statistical signal processing, multisensor multitarget data fusion, tracking, detection, and genomic signal processing.

Ahmed M. ElBakly received the BS in electrical engineering and the MS in mathematics engineering from the Military Technical College, Cairo, Egypt, in 1987 and 1992, respectively. He received the PhD in electrical engineering from Virginia Tech. University, USA, in 1999. He is currently working as an assistant professor in basic and applied science in the College of Engineering and Technology, Arab Academy for Science, Technology, and Maritime Transport, Cairo, Egypt. His research interests include electronics, communications, camouflage, and absorbing materials applications.

Mohamed H.A. Azeem received the BS and MS in electrical engineering from the Military Technical College, Cairo, Egypt, in 1985 and 1992, respectively. He received the PhD in electrical engineering from Kent University, UK, in 1999. He is currently working as an associate professor in the Electronic Engineering Department in the Military Technical College, Cairo, Egypt. His research interests include electronics, microwave circuits, and radar applications.

Gamal A. Hamid received the BS from the Military Technical College, Cairo, Egypt, in 1983, MS from Cairo University in 1988, and PhD from Military Technical College in 1999, in electrical engineering. He is currently working as an associative professor in the Electrical Engineering Department in the Military Technical College, Cairo, Egypt. His research interests include wireless personal communications, mobile and indoor radio communication, multipath channel characterization, land mobile satellite communication, and diversity and MIMO techniques.